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Optimization of agent evacuation models using behavioral data from VR-based experiments

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Abstract: Agent modeling is an effective tool for making predictions about evacuation aspects of buildings. However, these models have various computation mechanisms with different outcomes, which affects their validity and potential application. This study aims to assess VR data based agent modeling as a source of reliable behavioral predictions regarding the process of evacuating humans from buildings in an emergency. To this end, the study compares different input settings of agent-based evacuation models (ABEMs), refining selected parameters to achieve better predictions about real evacuation behavior from buildings in emergencies. Five alternative models were calculated, whereby their key variables (quantities) were optimized based on empirical data from an original evacuation exercise conducted under real and virtual conditions. On the basis of a statistical analysis of the model outputs, this study found that VR-based agent modeling (ABEM) was a promising tool for making effective and ecologically valid evacuation predictions, as it matched real-world behavior and offered desirable variance in the data outputs necessary for practical applications.

Keywords: *agent-based evacuation model; virtual reality; virtual environments; indoor evacuation; evacuation behavior; agent modeling; navigation*

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1. Introduction

Artificial intelligence-based agent models are an effective tool for making predictions about processes that occur during the evacuation of humans from buildings. Nevertheless, the current models have many limitations [1], including the absence of difficult-to-access behavior and cognitive quantities as inputs for computing models. Recent advances in virtual reality (VR) have shown promise in simulations with regard to viable options for capturing behavioral data about actual human behavior during evacuations. Predictions about human evacuation behavior in real situations can be made on the basis of cost-effective and ecologically valid VR measurements [2]. Findings on human behavior in VR experiments can be transferred and incorporated into agent models in order to refine them. Most commercially used agent models are limited to direct ways of agent movement. They possess no cognitive or behavioral predictors, for example, they do not consider many of the specific cognitive and behavioral manifestations that occur in evacuees. Data on participant movement and decision-making processes from VR-based experiments may help promote the effectiveness and precision of agent models with regard to evacuation predictions, as human factors are fundamental variables in the outcomes of

building emergencies [3]. In this regard, evacuation behavior and related processes have been widely explored from several perspectives, including state-of-the-art technologies such as VR, AI, and agent-based evacuation models (ABEMs). ABEMs are used for various kinds of simulations in order to explore, visualize and predict potential scenarios in evacuating people from buildings. However, ABEMs usually work on the basis of artificial algorithms that calculate the spatio-temporal optimum of the agent movement (e.g., the shortest distance). Although smoothing algorithms offer somewhat more natural courses of movement [4] ABEMs usually neglect the fact that the dynamics and trajectories of human movement in real environments do not fully correspond to artificial calculations [1]. Evacuation is typically understood as a systematic movement of a person from a dangerous place to a designated assembly point, which means it is fundamentally a human-centered activity. It can be called path-search or aided wayfinding in unfamiliar indoor environments [5]. From this perspective, it is directly determined by individual human cognitive abilities and traits, including decision-making strategies, spatial skills, or aptitudes for understanding indoor environments [6; 7; 8]. A wide range of complex behavioral phenomena occur during human evacuation, such as prolonged reaction to fire alarms (pre-movement time) [3; 4; 9; 10; 11; 12] or the frequent use of retracing navigation strategy, whereby inexperienced individuals, in particular, evacuate by the same route they entered the building while ignoring evacuation signs [3; 4; 13; 14]. People also often use exits other than the prescribed emergency exits [15].

Evacuation behavior is also influenced by the contextual environmental information that is present at the time [16; 17]. Previous studies have analyzed the impact of the presence of navigation aids, signage, and landmarks [3; 4; 17; 18], light [19; 20], visual, auditory or olfactory cues that depend on the form of the threat that necessitates the evacuation [21; 22], and the affordances proposed by the environmental structure itself [13; 20; 23]. This has placed behavioral studies of individuals in the specific environment at the center of current research.

For effective prediction with regard to building designs, it is necessary to capture and incorporate human factors into evacuation models. For many reasons, evacuation drills focused on critical human factors cannot be conducted on a mass scale in critical structures such as hospitals, stadiums, shopping malls, or buildings that are still under construction. Digital models of buildings presented via virtual reality (VR) can be used to facilitate better visualization and spatial planning. VR-based experiments are ecologically valid, controllable [2] and potentially cost-effective ways of gathering behavioral data on human actions in a wide range of situations. VR seems to activate brain mechanisms similar to those that occur in the real world [24; 25]. In this regard, it has been found to effectively simulate real-world scenarios [26]. Virtual environments (VEs) provided via immersive head-mounted displays (HMDs) possess a high level of realism and allow for the non-invasive collection of behavioral data, which is further promoted by a controllable degree of VE interactivity [27] and activity-logging options [28; 29]. Moreover, VR-based experiments[1] can be easily performed in virtual buildings that do not currently exist (e.g., proposed buildings) [28; 30; 31; 32; 33] and can be applied for situations related to dynamic hazards, such as fire or the spread of toxins [34]. In this regard, Building Information Modelling (BIM) technology may be used to promote the effective design of VR environments, following the need for human-centered design assessment [35]. Conclusions drawn from these highly realistic experiments can be transferred to ABEMs and applicable predictions about construction relevant criteria can be made. On the other hand, negative effects such as cybersickness (i.e., nausea; [36]) or fatigue, which have been commonly reported with regard to the use of VR displays, constitute a major limitation for the mass-scale use of VR. As with other VR phenomena, cybersickness is frequently studied in the attempt to reduce its negative effects to a minimum.

[1] In this text, we use the term "VR experiments" instead of "VR simulations" to avoid potential confusion with "agent simulations".

In general, any model should simplify real phenomena to some extent in order to offer more effective insight and predictions about the subject of investigation. This simplification, however, questions the reliability of the model in question. The reliability of numeric models, including evacuation models, is determined by the process of their verification, validation, and calibration. Verification is a technical process whereby the theoretically calculated values are compared with the values provided by the model and which verifies the correct implementation of a mathematical problem that defines the solution of a given situation [37]. Validation determines the extent to which the model reliably represents reality. However, the diversity of real-world situations is problematical for the generalization of validation (i.e., the specific parameters of validation). Since the validation process used for one scenario cannot be generally applied to another one [38; 39], a calibration becomes an integral part of the model creation and the defining of its parameters (including the incorporation of, for example, population composition, specific movement or reaction time into the model as fundamental quantities). In this regard, five basic quantities were defined in order to achieve possible quantification of the processes mentioned above [40], namely, pre-movement time (e.g., reaction time to the alarm sounding), walking speed, exit use (i.e., the choice of exits based on specific features and situations), availability and route selection, and traffic flow.

On the basis of these quantities, it is possible to calibrate and subsequently validate a model. However, the capturing of these parameters empirically in the real environment is a challenging issue, which moves it away from engineering practice. Real evacuation drills are usually not cost-effective simulation tools (in terms of time, expense, logistics, and security). In the worst case, the target structure may still be at the stage of project documentation, in which case any direct measurement would be impossible. For calibration purposes, data from other experiments can be transferred and used [41; 42], but the validation is often overlooked. In this regard, VR experiments are considered to have great potential, since they offer a unique opportunity to obtain the necessary data even when the building or site in question is still in its design phase, or where the actual implementation of the evacuation experiment is not possible for security or organizational reasons. However, the reliability and usability of specific quantities identified in VR-based research still remains unclear and needs to be explored in relation to the technical opportunities and limits of VR tools and the specific correspondence of VR-generated experiments to real evacuation behavior.

This paper presents a comparison of several input settings of the Pathfinder ABEM, in which various quantities were alternated in order to achieve better suitability for predicting evacuation behavior. To optimize the key quantities, we build on previous research into cognitive and behavioral aspects of human evacuation behavior in real and virtual conditions that was conducted by Kubíček and his colleagues [43]. On the basis of obtained empirical dataset from this research [44], this study aims to optimize the suggested models with empirical data and statistically compare the outcomes of the final models in order to assess the potential viability of VR technologies in agent evacuation modeling.

2. Materials and Methods

In this section, we first describe the technical specification of the ABEM model Pathfinder, which was used in this study. Secondly, we describe the data obtained from the empirical research [44] that were used to optimize the model. The Model Quantities subsection identifies individual behavioral metrics that could be quantified based on the collected data. The exact method and values of setting the input parameters of the models are also provided. The final subsection describes in detail the process of model calculations. The comparison of the calculated models is intended to optimize the Pathfinder model. The procedure is depicted in the Figure 1.

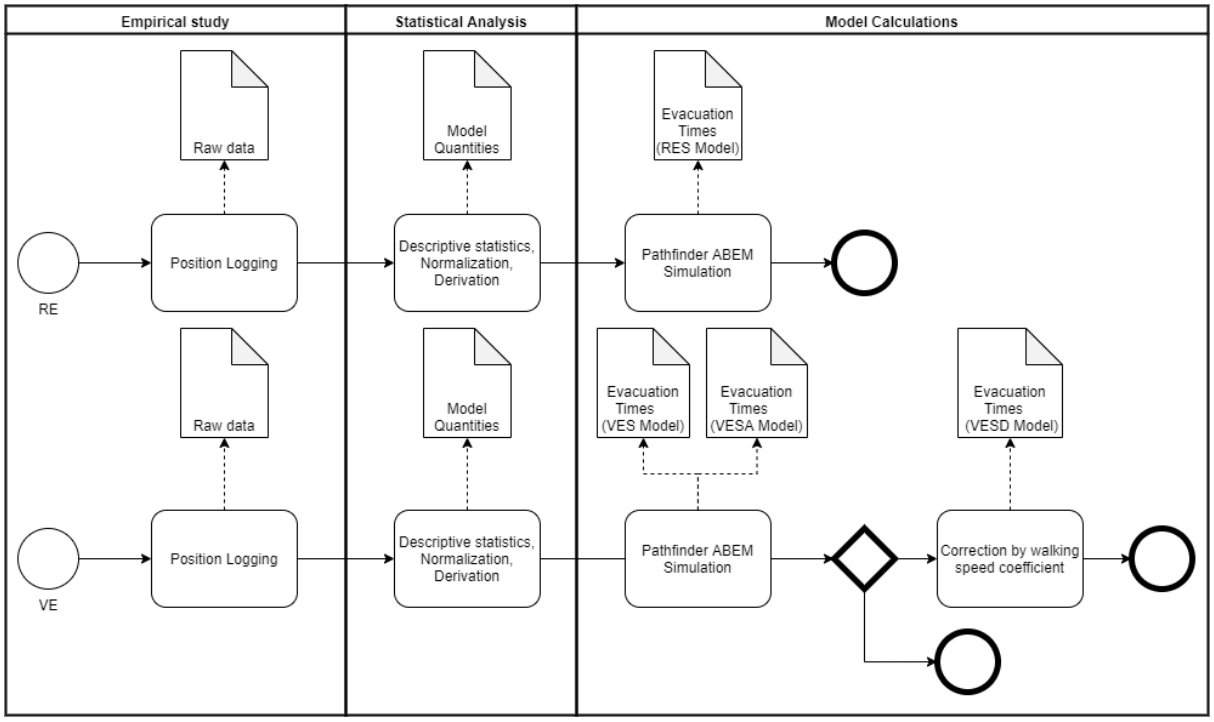

Figure 1. The diagram of model calculations process.

2.1. Software

This study used Pathfinder software (version 2021.2.0525 x64), which was developed by Thunderhead Engineering company. Research has shown that Pathfinder is the most used pedestrian evacuation model in academic and industrial fields [45]. The model consists of three modules: a graphical user interface (GUI), a simulator, and a 3D results viewer. GUI is primarily used to create model geometry and model calibration. Supported input geometry file formats include BIM formats (ifc), 3D formats (dae, fbx) and 2D (dwg, dxf). After the geometry is imported, a triangulated navigation mesh is created. Agents are presented as autonomous entities with a predefined set of parameters (User Manual, [46]).

At the beginning of the simulation, for each agent there is an identified local exit in the actual room. Then Pathfinder uses the A* search algorithm [47] for generating seek curves in the navigation mesh (Technical Reference, [48]). Simulation can be performed in SFPE mode or STEERING mode. SFPE is based on a flow model, where walking speeds are determined by agent density in each room, and flow through the door is controlled by door width. In this model, agents can occupy the same point in the geometry and are not able to change their seek curve. The STEERING mode uses a combination of the steering mechanism and collision handling to control how each agent follows their seek curve (B-spline), making the movement of agents more natural and complex. In every time step, there is a calculation of the next position of the agents based on actual distance from other agents [48].

2.2. Data

The specific dataset [44] used for the model optimization was obtained from the original empirical experiment by Kubíček et al. [43]. The experiment compared the evacuation behavior of users in two different conditions: an evacuation from a real building (35 participants) and an evacuation from an equivalent virtual building (see Figure 2), which was modeled as a digital twin (38 participants), and therefore the data are an original

empirical dataset. The detailed methodology, experiment procedure, and statistical comparisons of the gathered observations on human behavior in real and virtual environments are processed and presented in a separate article [44]. In short, the participants in the evacuation experiments were instructed to navigate to a specific location in an unknown building, where they were forced to evacuate by the sounding of a fire alarm. Since the purpose of the experiment was to explore evacuation behavior and decision-making, participants were prevented from returning by the same route as they entered the building by the placing of an obstacle in their path, which forced participants to look for an alternative evacuation route. During the evacuation, the specific movement data of participants in terms of time and place were captured (an illustration of one participant's evacuation trajectory is displayed in Figure 3). From the gathered raw data, we derived detailed behavioral metrics about the participants' passages through the building. The obtained data were used to refine the output of the agent evacuation models (Pathfinder).

Figure 2. The real building (left) and its virtual twin (right) used for the evacuation.

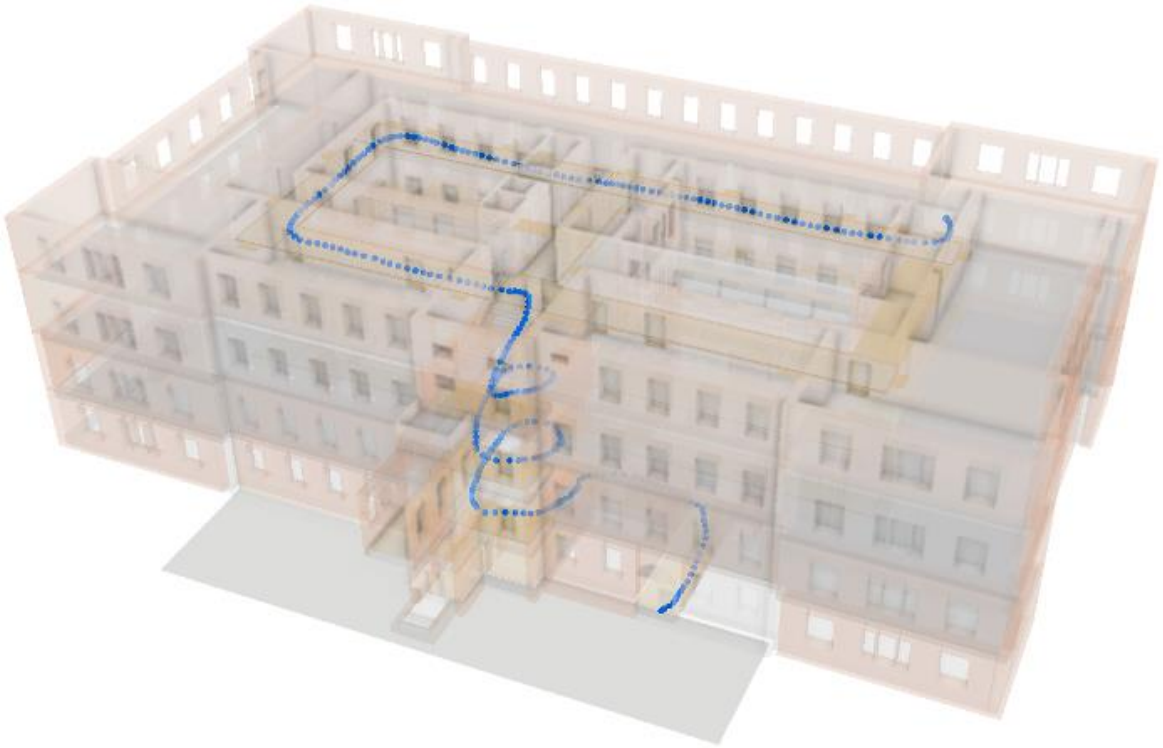

Figure 3. Illustration of the evacuation trajectory of one participant in the virtual model of building.

2.3. Model Quantities

Taking into account the options of current agent simulation tools, we selected key behavioral metrics obtained from the above-mentioned study by Kubíček et al. [43] to refine Pathfinder ABEM. Navigation movement and other behaviors in real environments, in comparison with virtual ones, are expected to vary based on the specific features of the environments [49; 50]. Previous research has suggested that VR technology limits human performance [51] in relation to the unnatural "involvement" of users in simulation scenarios [52], imperfect depiction, or problematic metaphors of movement [52]. The interface metaphor for movement in VR (i.e., the specific settings of movement control in the VR interface such as, for example, a keyboard or joystick) was particularly identified as problematic where a keyboard-mouse control interface was used [43]. Such a setup does not simulate real patterns of changes in speed (accelerations) in avatar movements and only offers either constant speed motion or standing.

In cognitive processes such as decision or reaction times and choice of exit, however, the assumptions as to their similarity in real and virtual environments suggested by previous studies [24; 54] seems to be supported [43]. In this case, convincing analogies were observed in the analyzed data, either in the overall averages of the measured variables or based directly on similar trends identified via visual analysis. For refining the models, we focused on the behavioral parameters that were identified as corresponding in real and virtual environments [43]. The parameters that were selected for the optimization of computed models will be presented in more detail (see Table 1 for a general comparison). The Pathfinder model allows us to reflect the distribution of the evacuees (agents) on the basis of gender at the input [46]. Therefore, all the values of input parameters used in this study reflect the specific gender distribution of participants in each experiment and are aggregated on that basis, if not stated otherwise.

General quantities:

- Pre-movement time (Alarm reaction time) [s]: When the alarm goes off in the emergency, people do not start to evacuate immediately, making it the key quantity in the estimation of the evacuation time. However, standard methods in the Czech engineering context as reflected by ČSN (Czech Technical Standards), do not usually consider this parameter [55]. The brain must initially process the perceived signal, and depending on the various environmental and individual aspects, there is a delay in the human reaction. Since this delay should be incorporated into artificial agent models, we consider its correction crucial in approaching the behavioral validity of the model. The pre-movement time (the time it took the participants to leave the room from the moment the alarm sounded) was set in the model on the basis of observations from Kubíček et al. [43].

- Free walking speed [m/s]: Speed was one of the metrics for which it was impossible to ensure comparable conditions between real and virtual environments (because of the above-mentioned movement interface metaphor). In the real environment, the speed of the participants was not limited in any way, while in the virtual environment, it was constant (which is related to the chosen method of movement control: a keyboard-mouse interface). To determine the free walking speed, the two longest segments of the corridor on the 4th floor were selected (the red corridors in Figure 4). In each segment, the total distance [m] and the time [s] traveled were monitored. Subsequently, the distance was divided by time, thus obtaining an average speed for each participant on both segments. Average speeds were aggregated based on gender for both segments and interpolated with a normal distribution (see Table 1), which served as the model input.

- Staircase walking speed [m/s]: It was possible to derive walking speed on the staircase route segments separately. The participants' speed on the staircase was derived from six identical flights of the main staircase. The two farthest measured points of the trajectory were determined on each flight, then the distance between them [m] and the time [s] traveled were calculated. Based on this, an average speed on the given flight of stairs was obtained. Subsequently, the average speeds were aggregated on the basis of gender for all flights of the staircase. After dividing by the average free walking speed, a coefficient was obtained (see Table 1) by which the free walking speed of movement assigned to the individual agents was multiplied for the staircase route segments.

- Acceleration [s]: This is the time it takes for the agent to reach maximum speed. This was not possible to determine on the basis of the empirical experiment, so it was estimated according to the default setting. With regard to the features of the VE setting (where the speed is constant and limited by movement controls), the acceleration was not set for models based on the virtual condition.

- Distance from walls [m]: During the building walkthrough, agents in models follow the ideal trajectory of movement, i.e., the most spatially effective path. Human movement in buildings does not copy this ideal trajectory. In the study by Kubíček et al. [43], the corners of the building were identified (C1-5 in Figure 4), for which the minimum distance at which participants approached the individual corners was recorded. A normal distribution with the parameters described in Table 1 was then applied to the aggregated data, reflected by gender.

- Distance from central staircase pillars [m]: The minimum distance participants maintained from the corners of the columns on the stairs was monitored (S1-12 in Figure 4). The subsequent determination procedure for the model input was identical to that relating to distance from walls.

Building specific quantities:

- Decision time on predefined decision points [s]: The decision process is a crucial human factor, which has been found to be similar in real and virtual evacuation experiments, although it is not usually considered in agent simulations. Since the decision time and the choice of route depend on the specific spatial configuration of the building, we cannot abstract the general parameters applicable for every simulation scenario. Three decision points were identified and approximated to polygons on the evacuation route (see Figure 4). The first decision point (A) was a stop at the cage that blocked the route that the participants had previously used to enter the lecture room. The second stop (B) was the junction on the 4th floor, where it was possible to turn towards the elevator (which it was forbidden to use during the evacuation) or go down the stairs. The third decision point (C) was the point at the bottom of the stairs on the 1st floor, where the paths separated into an officially marked evacuation route and a route returning the same way the participants had previously entered the building. In the study of Stachoň et al. (manuscript), the time [s] that participants spent in these polygons was monitored and used as input for our calculations for the models. In addition, where the participants made a longer deviation from the route at these points (usually towards the elevator), it was manually introduced into the model (see Table 1).

- Retracing strategy [boolean]: As with the previous parameter, even retracing depends on the various aspects of the building, although the ratio of people who used the retracing strategy to leave the building was similar in the real and virtual environments (Stachoň et al., manuscript). Computed models reflect the retracing behavior of participants by assigning the specific exits to individual agents. The specific distribution is depicted in Table 1.

Table 1. Explicit values of input parameters for the model simulations. (Several values were taken from the data collected in [43]. For an exact explanation, see the descriptions of the parameters above.)

Input parameters	**Default Settings**	**Real Evacuation**		**Virtual Evacuation**	
Gender	-	43 % men	57 % women	58 % men	42 % women
Alarm reaction time [s] *mean (SD)* *[min; max]*	0 [s]	6.07 (2.38) [2.5; 11]	5.53 (2.07) [3; 10.5]	6.89 (3.74) [3.31; 17.8]	6.93 (3.98) [3.16; 16.5]
Free walking speed [m/s] *mean (SD)* *[min; max]*	1.19	1.82 (0.278) [1.42; 2.25]	1.78 (0.379) [1.3; 2.68]	2.22 (0.158) [1.96; 2.54]	2.09 (0.223) [1.66; 2.34]
Staircase walking speed [m/s] *mean [m/s] (coeficient [-])*	1.19 (1)	1.294 (0.71)	1.176 (0.66)	2.22 (1)	2.09 (1)
Acceleration [s]	1.1	1.1	1.1	0	0
Distance from walls [m] *mean (SD)* *[min; max]*	0.15	0.922 (0.245) [0.559; 1.41]	0.894 (0.279) [0.465; 1.38]	0.91 (0.333) [0.387; 1.53]	0.9 (0.284) [0.372; 1.44]
Distance from staircase central pillars [m]	0.15	0.642 (0.183) [0.409; 0.954]	0.647 (0.211) [0.37; 1.00]	0.676 (0.239) [0.29; 1.06]	0.625 (0.242) [0.286; 1.03]

mean (SD) *[min; max]*					
Decision time in front of the cage *time [s] (distribution [%])*	-	0-5 (33) 5-10 (40) 10-15 (7) 15-20 (13) 45-50 (7)	0-5 (30) 5-10 (30) 10-15 (20) 15-20 (5) 20-25 (10) 50-55 (5)	0-5 (50) 5-10 (27.5) 10-15 (5) 15-20 (12.5) 30-35 (5)	0-5 (25) 5-10 (50) 10-15 (13) 15-20 (6) 35-40 (6)
Decision time in front of the stairs on 4. floor *time [s] (distribution [%])*	-	0 (86.6) 5 (6.7) Try to use elevator (6.7)	0 (95) Try to use elevator (5)	0 (87) Try to use elevator (13)	0 (93.75) Try to use elevator (6.25)
Decision time in front of the stairs on 1. floor *time [s] (distribution [%])*	-	0-2 (53) 2-4 (26) 4-6 (14) 8-10 (7)	0-1 (50) 2-4 (25) 4-6 (5) 6-8 (20)	0-2 (55) 2-4 (45)	0-2 (68.5) 2-4 (18.5) 4-6 (13)
Retracing [boolean]	-	80 % yes, 20 % no	70 % yes, 30 % no	36.4 % yes, 63.6 % no	43.8 % yes, 56.2 % no

2.4. Evacuation Model Computation and Simulations

The Pathfinder agent model at the entrance requires the geometry of the building and allows the setting of input parameters that further distinguish the character of individual agents. The specific geometry of the model was created based on the 3D building documentation (.fbx) created in Revit Architecture. A simplified visualization of the evacuation path and adjoining corridors can be seen in Figure 4.

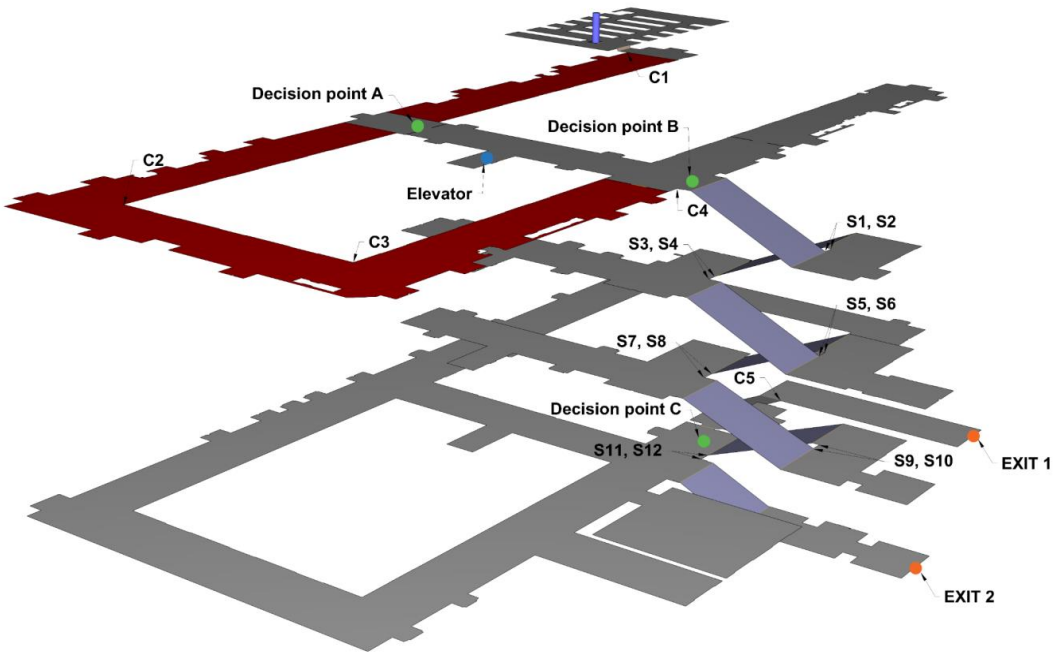

Figure 4. Visualization of the evacuation path and adjoining corridors.

The principal output of the models is the evacuation time, which is primarily dependent on walking speed and is the key measure in the evacuation predictions. However, walking speed is one of the factors where there is no equivalence when we compare the results obtained from empirical experiments performed in reality and virtual environments [44] due to different interface metaphors of movement. The input data for this study were taken from a VR experiment using a standard keyboard-mouse control interface, which limits the possibility of acceleration. The participant can either stand or move at a constant speed set at 3m/s.

Therefore, for the purposes of this study, the evacuation simulations were run with four overall input parameter settings. In the first, we kept the default settings (hereinafter referred to as Default Settings - DS model). In the second, to set the input parameters we used data obtained from an empirical experiment in a real environment (Real Evacuation Settings - RES model). In the third, we used data from an experiment in a virtual environment (Virtual Evacuation Settings - VES model). For the fourth simulation (Virtual Evacuation Settings Adjusted - VESA model), we used the same data as for the VES model, but the free and staircase walking speeds were adopted from the data collected in the real experiment (a real evacuation drill). Finally, we created a derived model (Virtual Evacuation Settings Derived - VESD model) from the VES model, in which we corrected the resulting evacuation time by a coefficient calculated as:

$$\frac{total\ average\ walking\ speed\ VE}{total\ average\ walking\ speed\ RE} = \frac{2.184\ m/s}{1.754\ m/s} = 1.245.$$

The input data for the simulations were generated by the Monte Carlo method [56]. In each file, every agent was assigned a unique random number (a so-called random seed) which generated the new parameter values in each simulation within the specified distributions (e.g., movement speed, see Table 1.) for each agent. This mechanism generates variations in the trajectories of the agents and calculated evacuation times, so the outcomes of the simulations could be subjected to statistical analysis. In this study, the number of simulations for the reality-based model and VR-based model was determined according to the number of participants in the original empirical experiment and also reflected the gender ratio. One simulation set included 35 simulations for the reality-based model and 38 simulations for the VR-based model. In total, 10 sets were simulated for each model (350 simulations for the reality-based model and 380 simulations for the VR-based model). The larger number of simulations ensured the stability of the median of the results (see Figure 5) and included all behavioral phenomena defined by the parameters in Table 1, even those that were not so numerous (e.g., trying to use an elevator). The models with default settings do not contain any parameter distribution, so there is no variability, and the number of simulations is not limited. However, 35 simulations were performed where the missing variability is seen.

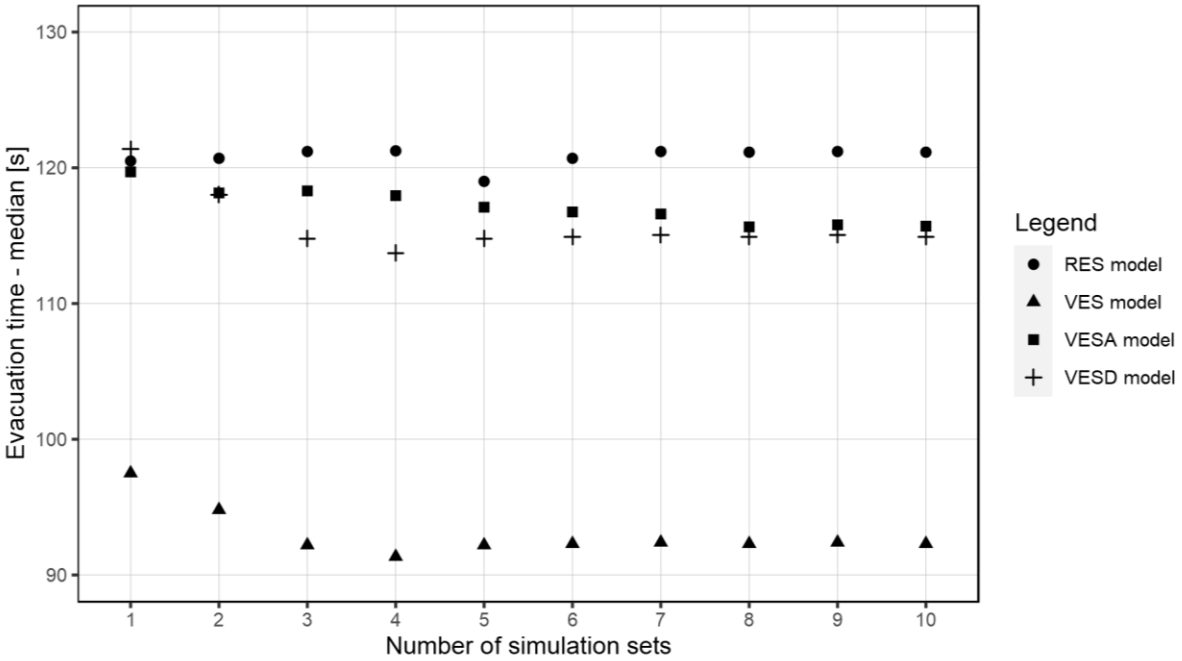

Figure 5. Dependence of evacuation time on the number of simulations for RES and VES models.

The key output of the simulations for this study was the total evacuation time. This is the time from the alarm sounding to reaching the exit and is crucial for most evacuation simulations. For this reason, it was selected as an assessment criterion and then became the subject of a comparison of the outputs of the models.

3. Results

In this section, the results from the comparison of the computed models are presented. The analysis was conducted using RStudio v. 1.4.1106 [57]. For visualizations, the ggplot2 [58] package was used. The resulting evacuation times from all models were tested for normality using the Shapiro-Wilk test. Since none of them exhibited normal distribution, we chose non-parametric ANOVA (Kruskal-Wallis test) and post hoc Dunn's tests with Holm's p-value adjustment for between model comparisons.

First, we observed that the simulated agent movement in the proposed models followed the real movement trajectories of the participants captured in the empirical experiment (see Figure 6). This means that during the simulations, agents visited similar spaces in the building as real people did, which allows for more detailed interpretations of the reliability of the predictions.

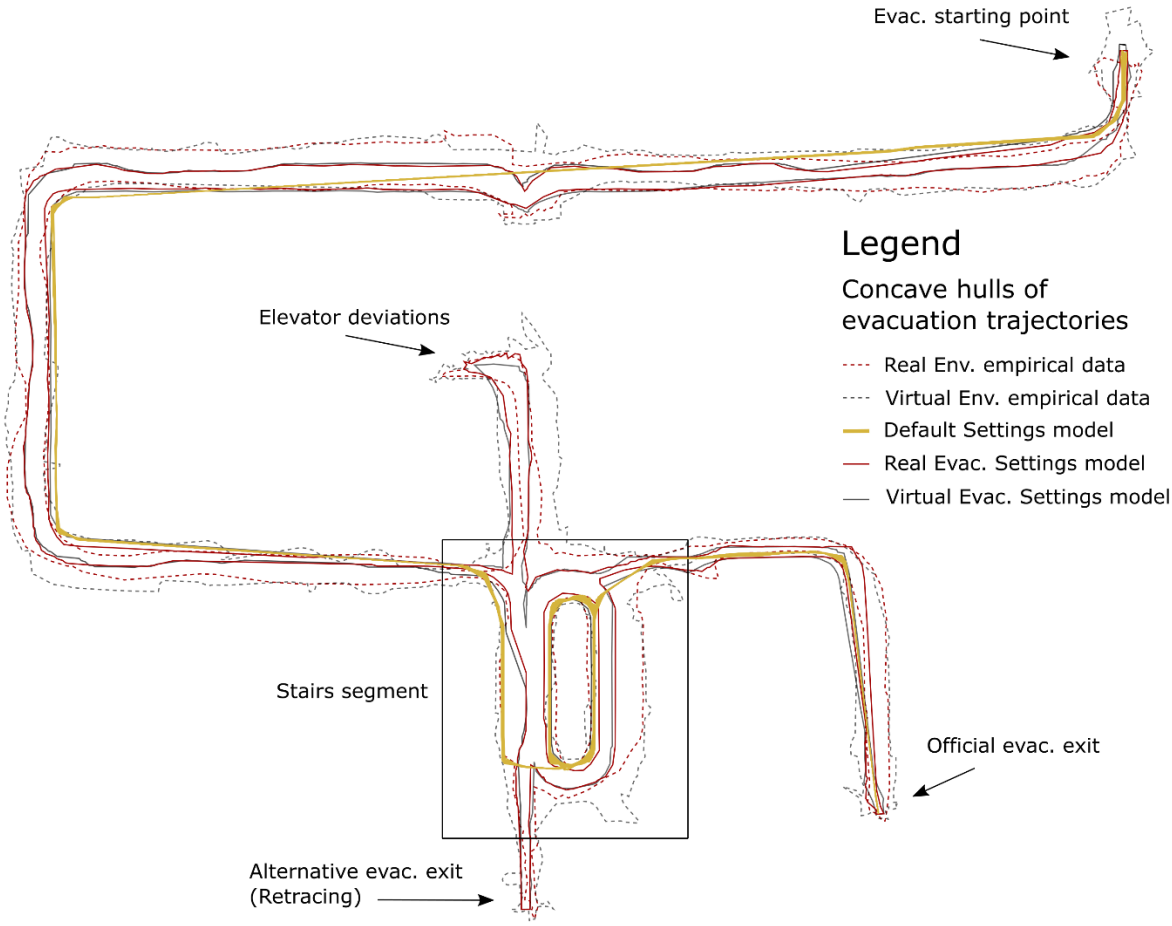

Figure 6. Visual comparison of participant and calculated agent trajectories.

The real (RE) and virtual (VE) empirical observations representing the behavior of real participants [44] are depicted in the graph (Figure 7) next to computed models involving agents, - i.e., the DS model, the RES model, the VES model, the VESA model, and the VESD model. The Kruskal-Wallis test indicated significant differences in evacuation times between observations ($\chi 2 = 2411.6$, df = 1, p-value < 0.001). The specific differences were calculated between individual conditions and are depicted in Figure 7, with the particular values shown in Table 2. The main trends are specified in more detail below.

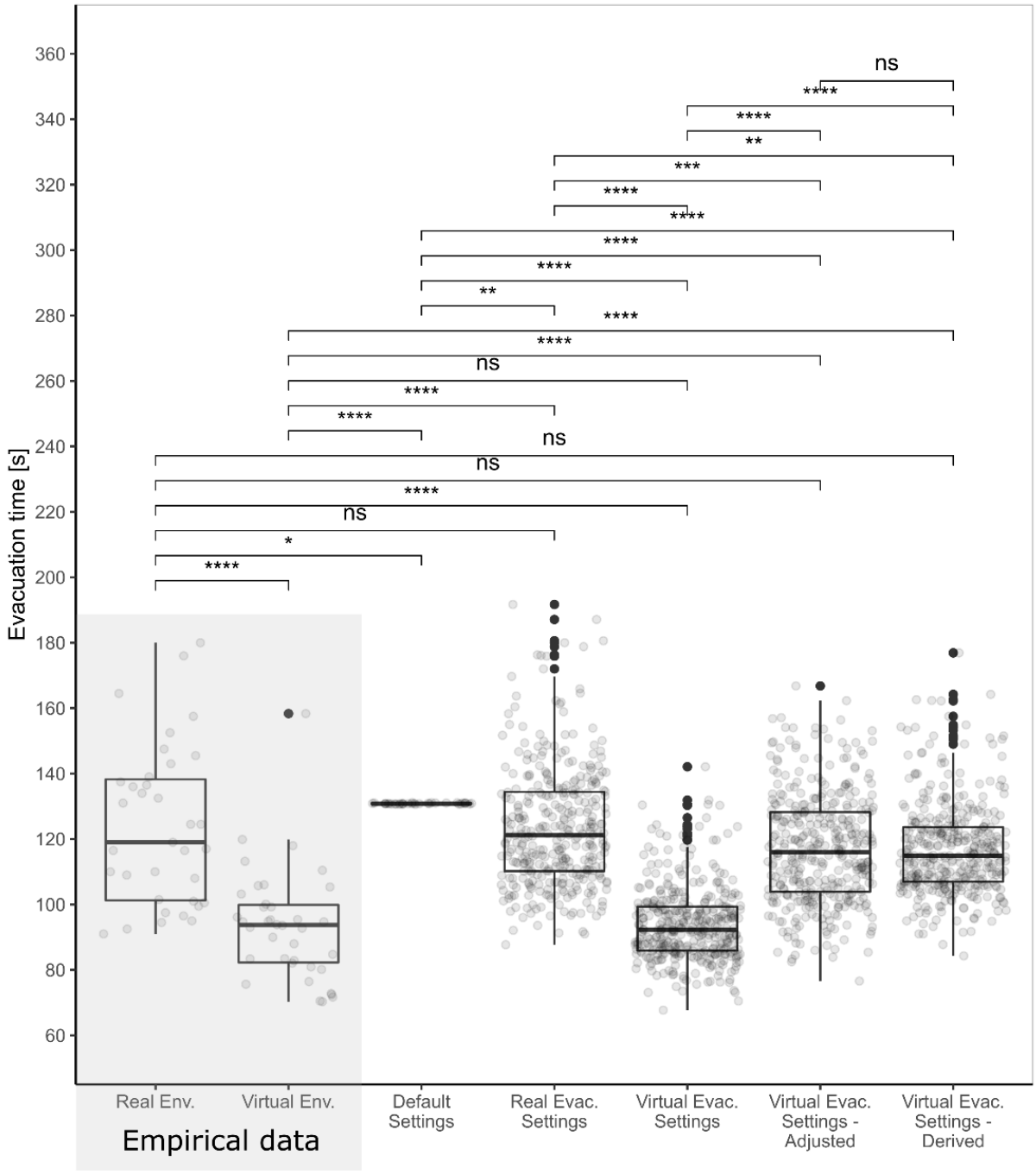

Figure 7. Box-plot depiction of computed models (including evacuation times from the real and virtual environments in [44]) which serve for the calibration of the agent models.

Table 8. Detailed results of post hoc Dunn's tests with Holm's p-value adjustment for between model comparison.

Model 1	Model 2	n 1	n 2	estimate	statistic	p-value	p-value adjusted	
RE	DS	35	35	325.214	2.948	0.00320	0.01917	*
RE	RES	35	350	51.300	0.627	0.53060	1.00000	ns
RE	VES	35	380	-680.059	-8.343	0.00000	0.00000	****
RE	VESA	35	380	-87.740	-1.076	0.28174	1.00000	ns
RE	VESD	35	380	-79.471	-0.975	0.32958	1.00000	ns

VE	DS	38	35	994.230	9.197	0.00000	0.00000	****
VE	RES	38	350	720.315	9.139	0.00000	0.00000	****
VE	VES	38	380	-11.043	-0.141	0.88814	1.00000	ns
VE	VESA	38	380	581.275	7.404	0.00000	0.00000	****
VE	VESD	38	380	589.545	7.509	0.00000	0.00000	****
DS	RES	35	350	-273.914	-3.348	0.00081	0.00569	**
DS	VES	35	380	-1005.273	-12.333	0.00000	0.00000	****
DS	VESA	35	380	-412.955	-5.066	0.00000	0.00000	****
DS	VESD	35	380	-404.685	-4.965	0.00000	0.00001	****
RES	VES	350	380	-731.359	-21.393	0.00000	0.00000	****
RES	VESA	350	380	-139.040	-4.067	0.00005	0.00043	***
RES	VESD	350	380	-130.771	-3.825	0.00013	0.00105	**
VES	VESA	380	380	592.318	17.693	0.00000	0.00000	****
VES	VESD	380	380	600.588	17.940	0.00000	0.00000	****
VESA	VESD	380	380	8.270	0.247	0.80489	1.00000	ns

The output evacuation times from the computed agent models were statistically compared with empirically obtained data from experiments with real people in both real and virtual environments [44]. As found in [44], data showed that evacuation times in the real condition (RE; m = 123.93 s; med = 119 s; sd = 24.39 s) differed significantly from the virtual condition (VE; m = 93.38 s; med = 93.73 s; sd = 17.06 s). Dunn's post hoc tests revealed that the evacuation times in the real condition differed significantly ($p < 0.01$) from the DS model (m = 130.84 s; med = 130.8 s; sd = 0.14 s). The evacuation times calculated by the model seem to be overestimated, and they do not fit the real observations. In reality, participants left the building faster on average, but with a very high variance in exit times. The total evacuation time for real hazards is determined by the last evacuees. When we consider the variance in evacuation times, the observed evidence shows that the final evacuation time was longer in reality (RE) taking into account the slowest evacuees. This variance, which is lacking in the DS model, makes the original ABEM informationally poorer, since it does not offer predictions about upper limit evacuation values (or specific outliers) that are represented by the slowest evacuees.

The models computed on the basis of the given empirical data exhibited several trends. As expected, the RES model (m = 123.63 s; med = 121.15 s; sd = 18.50 s), which was generated on the basis of data obtained from the real condition (RE; m = 123.93 s; med = 119 s; sd = 24.39 s), corresponds substantially to the real behavior of the participants. However, as seen in Figure 7, the VES model (m = 93.98 s; med = 92.3 s; sd = 11.36 s), which was generated on the basis of data from the virtual condition, differs significantly ($p < 0.001$) from the real condition (RE; m = 123.93 s; med = 119 s; sd = 24.39 s). On the other hand, both of the generated models that were based on VR data and corrected (i.e., the VESD model and the VESA model) corresponded to the real evacuation behavior (RE), which is an encouraging finding. Post hoc tests failed to identify any difference between the VESD model (m = 117.01 s; med= 114.91 s; sd = 14.15 s) and the VESA model (m = 117.01 s; med = 115.95 s; sd = 16.79 s), and neither of them significantly differed from the real condition (RE; m = 123.93 s; med = 119 s; sd = 24.39 s). This suggests that there is a correspondence between the real behavior of evacuees during evacuation drills and the simulated agent behavior computed on the corrected VR-based models.

4. Discussion

Our analysis of the computed models highlighted a number of significant trends. Most importantly, we identified that participants in the experiment conducted in the real building (RE) evacuated significantly faster ($p < 0.01$) than agents from the Pathfinder ABEM with default settings (DS model). This suggests that there is limited correspondence between the behavior of the people in real conditions and the agent simulation and supports previous concerns about the adequacy of the artificial parameter calculations [1]. This deficiency needs to be addressed by the use of ecologically reliable data in agent modeling in order to make better predictions about human evacuation behavior in buildings. As discussed above, conducting real evacuation drills to gather the necessary data to make model optimizations remains complicated for several reasons [29; 30]. One of the main aims of this study was to assess accessible VR-based data as an input for agent modeling. The empirical study by Stachoň et al. [44] identified significant differences in evacuation times between participants in real and virtual evacuations, where participants in the virtual building evacuated considerably faster than those in the real building. The same difference ($p < 0.001$) was observed in the case of the VES model when compared to the real evacuation. This difference was expected due to the movement interface metaphor used in the virtual experiment (default walking speed), which in the study by Kubíček et al. [43] was set as constant for the VR experiment and considerably influenced the evacuation speed of participants. This rather technical limitation has already been reflected in previous research [43] and further research is necessary in this area. In this regard, in this study, we conclude that virtual experiments per se should not be considered a fully adequate substitute for real evacuation drills, and only limited conclusions about evacuation behavior can be drawn on the basis of raw VR observations.

However, the identified trends in the outcomes of the corrected VR-based models (the VESA model and the VESD model) clearly support the case for the computation and possible use of agent models based on VR data, but with necessary corrections. Both the VESD and the VESA models corresponded to real evacuation behavior (RE), whereby the model simulations provided similar evacuation time and movement trajectory outcomes. Since the agents in the data-corrected VR-based models followed trajectories that were observed in reality, the models produced evacuation time variance similar to real behavior, which provides evidence to support the similarity of the selected behavioral and cognitive processes (parameters) demonstrated in real and virtual environments [24; 26]. These findings represent an exciting direction for future research, whereby virtual reality-based experiments can be adjusted for ABEMs as a cost-effective, productive, easily available, and ecologically valid tool for making predictions about the evacuation behavior of people in various types of buildings. From this perspective, VR-based ABEMs can be seen as significant future trend, which is worthy of more detailed research. As demonstrated above, the VR-based agent models corrected by movement speed offer a great deal of reliability, since they approximate real evacuation processes, including movement trajectories, and offer better predictions for practical use. This study failed to identify any significant difference between the VESD model and the VESA model. Both corrected models generated from VR data corresponded to the real observation of behavior to a similar extent, which offers at least two possible methods of computation for VR-based agent models. The first method is (1) correction of the VR data on the basis of the real walking speed obtained from a specific real evacuation drill in the building under evaluation, which serves as a direct input parameter for model simulation. This method is limited by the need for a physically existing building and is therefore unsuitable in cases where the safety of a building is being assessed at the design stage. The second method is (2) post-processing correction of the VR-based model outputs. The correction can be done by theory-based or empirically-based standardized coefficients (the latter was done in the case of the VESD model). This method of correction was found to be a valid, reliable, and applicable solution for making predictions about evacuation aspects of buildings, since it corresponded to real evacuation behavior. The key future direction of research is the use of interface metaphor for movement, which in VR environments allows for movement

that is completely equivalent to reality. However, this will involve advanced haptic interfaces and will require considerable technological and monetary resources. More in-depth discussion of this issue, however, goes beyond the scope of this study, since it focused exclusively on the application of previously collected data [44] for the optimization of agent models. In the context of this study, we offer two possible methods of approximating such models to real behavior on the basis of movement speed correction.

VR-based models can be seen as valid tools, since they incorporate real behavioral patterns. We observed a similarity between real and agent movement insofar as the movement of agents in the simulations followed real trajectories. This provides persuasive argumentation for the equivalence of these models to reality, but for future predictions it also allows us to consider minority phenomena such as detours or getting lost during the evacuation, which demonstrably happens in reality, but is not usually incorporated into default models. These (usually minority) phenomena should be further explored with regard to critical evacuation contexts such as fractional effective dose (FED) or the slowest evacuees (which will be discussed below). Nevertheless, they greatly surpass the default models, because the original default ABEMs (DS model) did not provide any variance of the predicted evacuation times, and therefore, in the context of this study, they were perceived to be inferior to the models based on empirical data. The default ABEMs lack functionality, as they do not provide, for example, the upper quantiles (e.g., preset at 95%), since they only generate measures of central tendency. Computed corrected VR-based models (the VES model and the VESA model) provided information involving the distribution of evacuation times including potential outliers (i.e., extremely slow people), whose safety it is also necessary to secure. Statistically speaking, evacuees present in the third quartile of evacuation times (the longest) represent the most vulnerable population, since they are last to exit the building, so evacuation procedures should be particularly focused on this group. In order to do this, empirical observations of evacuation drills are necessary to capture potential anomalies and outliers, and in this respect VR can significantly promote their availability. Moreover, a significant benefit of virtual reality experiments for practical applications is the controllable, safe, and dynamic modulation of the environment for empirical testing. The use of dynamic models to study, for example, fires [34] or the spread of toxins can help to identify deviations in the behavior patterns of individuals that differ from ideal or assumed movement trajectories (i.e., passage route), and constitute an area for future research. These movement deviations may cause delays and outlying values in decision-making times specifically in relation to critical points in the area of the researchers' interest (e.g., blocked passage etc.). Such deviations in the evacuation process may have a significant influence on exposure to toxic substances or temperature and thus on the final fractional effective dose (FED). VR-based models preserve the above-discussed advantages of VR evacuation experiments, such as cost-effectiveness, speed, dynamic modulation, accessibility, and data logging options [28]. More importantly, they can also be applied during the planning phase of buildings [30]. As for the primary limitations of VR applications in this field, they remain the commonly reported issues such as cybersickness [36], i.e., the feeling of nausea when using virtual displays such as HMDs, especially when moving, which causes considerable experiment mortality and therefore necessitates larger sample sizes. Moreover, the model data optimization is determined by the specific nature of the research sample and it is necessary to take into account the fact that such ABEM predictions apply primarily for the studied populations. With regard to the above, in order to follow principles of external validity, any further empirical measurements made for the purpose of potential application in real practice should include an adequate representation of the target population. Regardless of the above-mentioned limitations, we conclude that the results of this study support the viability of reliable and ecologically valid empirical inputs from virtual experiments [2] for agent modeling and ABEM creation. Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working

hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5. Conclusions

This study presents a comparison of several input settings of agent-based evacuation models (ABEM) in order to assess their suitability for predicting evacuation behavior in buildings. Various quantity settings involving VR-based data on human evacuation behavior that was obtained in real and virtual evacuation drills [43] were used to refine ABEMs. In this study, we found VR-based experiments to be a very promising source of data for refining and optimizing agent evacuation models (ABEMs). The main outcome of the study highlights the great potential of the outcomes of virtual experiments as data for incorporating into agent models, even though there is a necessity for the correction of selected parameters (specifically movement speed). VR-based evacuations can be used to gather valid data about the specific variability of movement trajectories in buildings which can easily be incorporated into agent models. In addition to the more precise computation of evacuation times as the main output of agent simulations, the specific movement trajectories can have a major impact on evacuation courses and therefore, for example, exposure to fire or toxic substances, whose specific profile can now be identified within an agent simulation more easily. Moreover, as we identified deficiencies in real and virtual evacuation drills, with the use of empirical observations we formulated suggestions as to how to correct the speed of movement in VR experiments so it corresponds to real conditions. Empirical data obtained from VR experiments and corrected with respect to movement speed was incorporated into agent modeling, where, in contrast to the default models, we were able to observe variability in the individual evacuation walkthrough of agents. This is a key insight into the issue of peripheral groups of evacuees (e.g., those that are slow or lost), who represent the most vulnerable and thus critical group of evacuees in the case of emergency situations in buildings.

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References

1. Kuligowski, E. D. & Peacock, R. D.: A Review of Building Evacuation Models. National Institute of Standards and Technology, 2005.
2. Veling, W.; Counotte, J.; Pot-Kolder, R.; van Os, J.; van der Gaag, M. Childhood trauma, psychosis liability and social stress reactivity: a virtual reality study. *Psychological Medicine* 2016, *46*, 3339–3348.
3. Proulx, G. Occupant behaviour and evacuation. In *Proceedings of the 9th International Fire Protection Symposium*, Proceedings of the 9th International Fire Protection Seminar, Munich, Germany, 2001; 219–232.
4. Johnson, C. Lessons from the evacuation of the world trade centre, 9/11 2001 for the development of computer-based simulations. *Cognition, Technology & Work* 2005, *7*(4), 214–240.
5. Wiener, J.M.; Büchner, S.J.; Hölscher, C. Taxonomy of human wayfinding tasks: A knowledge-based approach. *Spatial Cognition & Computation* 2009, *9*(2), 152–165.
6. Cao, L.; Lin, J.; Li, N. A virtual reality based study of indoor fire evacuation after active or passive spatial exploration. *Computers In Human Behavior* 2019, *90*, 37–45.
7. Golledge, R.G. *Wayfinding behavior: cognitive mapping and other spatial processes*. 1st ed.; Johns Hopkins University Press: Baltimore, Maryland, United States, 1999.
8. Maguire, E.A.; Burgess, N.; Donnett, J. G.; Frackowiak, R.S.; Frith, C.D.; O'Keefe, J. Knowing where and getting there: A human navigation network. *Science* 1998, *280*(5365), 921–924.
9. Geyer, T.; Bellamy, L.J.; Max-Lino, R.; Harrison, P.I.; Bahrami, Z.; Modha, B. An evaluation of the effectiveness of the components of informative fire warning systems. In *Safety in the built environment*; Sime, J. D., Ed.; E. & F.N. Spon: New York, New York, United States, 1988; pp. 36–47.
10. Proulx, G.; Sime, J.D. To prevent 'panic' in an underground emergency: Why not tell people the truth? *Fire Safety Science* 1991, *3*, 843–852.
11. Proulx, G.; Fahy, R. The time delay to start evacuation: Review of five case studies. *Fire Safety Science* 1997, *5*, 783–794.
12. Purser, D.A.; Bensilum, M. Quantification of behaviour for engineering design standards and escape time calculations. *Safety Science* 2001, *38*(2), 157–182.
13. Snopková, D.; Ugwitz, P.; Stachoň, Z.; Hladík, J.; Juřík, V.; Kvarda, O.; Kubíček, P. Retracing evacuation strategy: A virtual reality game-based investigation into the influence of building's spatial configuration in an emergency. *Spatial Cognition & Computation* 2021, 1–21.
14. Kurkjian, S., Ebbert, S., & Farragher, T. *Behind the Rhode Island nightclub fire: Series of errors sealed crowd's fate*. The Boston Globe 2003. http://archive.boston.com/news/packages/nightclub_fire/Series_of_errors_sealed_crowd_s_fate.shtml
15. Wood, P.G. The behaviour of people in fires. *Fire Research Notes* 1972, 953.
16. Kinateder, M.; Comunale, B.; Warren, W. Exit choice in an emergency evacuation scenario is influenced by exit familiarity and neighbor behavior. *Safety Science* 2018, *106*, 170–175.
17. Arthur, P.; Passini, R. *Wayfinding: People, Signs and Architecture*; Focus Strategic Communications Inc.: Brantford, Ontario, Canada, 2002.
18. Xie, H.; Filippidis, L.; Galea, E.R.; Blackshields, D.; Lawrence, P.J. Experimental analysis of the effectiveness of emergency signage and its implementation in evacuation simulation. *Fire and Materials* 2011, *36*(5–6), 367–382.

19. Taylor, L.H., Sucov, E.W.: The Movement of People toward Lights. *Journal of the Illuminating Engineering Society* 1974, 3, 237-241.
20. Vilar, E.; Rebelo, F.; Noriega, P.; Teles, J.; Mayhorn, C. The influence of environmental features on route selection in an emergency situation. *Applied Ergonomics* 2013, 44(4), pp. 618-627. https://doi:10.1016/j.apergo.2012.12.002
21. Shih, N-J.; Lin, C-Y.; Yang, C-H. A virtual-reality-based feasibility study of evacuation time compared to the traditional calculation method. *Fire Safety Journal* 2000, 34(4).
22. Kobes, M.; Helsloot, I.; De Vries, B.; Post, J. Exit choice, (pre-)movement time and (pre-)evacuation behaviour in hotel fire evacuation – behavioural analysis and validation of the use of serious gaming in experimental research. *Procedia Eng.* 2010, *3*, 37–51.
23. Hölscher, C.; Meilinger, T.; Vrachliotis, G.; Brösamle, M.; Knuaff, M. Finding the way inside: Linking architectural design analysis and cognitive processes. In *Spatial Cognition IV – Reasoning, action, interaction*; Freksa, C.; Knauff, M.; Krieg-Brüchner, B; Nebel, B.; Barkowsky, T., Eds.; Springer-Verlag: Berlin, Germany, 2005, pp. 103–121.
24. Alcañiz, M.; Rey, B.; Tembl, J.; Parkhutik, V. A Neuroscience Approach to Virtual Reality Experience Using Transcranial Doppler Monitoring. *Presence: Teleoperators And Virtual Environments* 2009, *18*(2), 97–111.
25. Wilson, P.N. Use of virtual reality computing in spatial learning research. In *A handbook of spatial research paradigms and methodologies, Vol. 1. Spatial cognition in the child and adult*; Foreman, N.; Gillet, R., Eds.; Psychology Press/Erlbaum (UK) Taylor & Francis: United Kingdom, 1997, pp. 181–206.
26. Paradis, M.A.; Nicolas, T.; Gaugne, R.; Barreau, J.B.; Auger, R.; Gouranton, V. Making Virtual Archeology Great Again (without scientific compromise). *The International Archives Of The Photogrammetry, Remote Sensing And Spatial Information Sciences* 2019, XLII-2/W15, 879–886.
27. Fuad, M. XR Interaction Toolkit Preview Package is here. Unity Technologies Blog 2019. https://blogs.unity3d.com/2019/12/17/xr-interaction-toolkit-preview-package-is-here/
28. Ugwitz, P.; Juřík, V.; Herman, L.; Stachoň, Z.; Kubíček, P.; Šašinka, Č. Spatial analysis of navigation in virtual geographic environments. *Applied Sciences* 2019, *9*(9), 1873.
29. Ugwitz, P.; Šašinková, A.; Šašinka, Č.; Stachoň, Z.; Juřík, V. Toggle toolkit: A tool for conducting experiments in Unity virtual environments. *Behavior Research Methods* 2021, *53*(4), 1581–1591.
30. Kuliga, S.; Thrash, T.; Dalton, R.C.; Hölscher, C.Virtual reality as an empirical research tool — Exploring user experience in a real building and a corresponding virtual model. *Computers, Environment And Urban Systems* 2015, *54*, 363–375.
31. Abras, C.; Maloney-Krichmar, D.; Preece, J. User-Centered Design. In *Encyclopedia of Human-Computer Interaction*; Bainbridge, W. S., Ed.; Berkshire Publishing Group LLC: Great Barrington, Massachusetts, United States, 2004; Volume 2.
32. Vilar, E.; Rebelo, F. Virtual Reality in Wayfinding Studies. In *Advances in Cognitive Ergonomics*; Kaber, D.B., Boy, G., Eds.; CRC Press: Boca Raton, Florida, United States, 2010; pp 802–811.
33. Morganti, F.; Carassa, A.; Geminiani, G. Planning optimal paths: A simple assessment of survey spatial knowledge in virtual environments. *Computers In Human Behavior* 2007, *23*(4), 1982–1996.
34. Kinateder, M.; Ronchi, E.; Nilsson, D.; Kobes, M.; Müller, M.; Pauli, P.; Mülberger, A. Virtual Reality for Fire Evacuation Research. In *Federated Conference on Computer Science and Information Systems*, Proceedings of the 1st Complex Events and Information Modelling at the Federated Conference on

Computer Science and Information Systems, Warsaw, Poland, 2014; Krasuski, A.; Rein, G., Eds.; IEEE – Institute of Electrical and Electronics Engineers Inc.: Piscataway, New Jersey, United States, 2014, pp. 313–321.

35. Bille, R.; Smith, S.P., Maund, K., Brewer, G. Extending Building Information Models into Game Engines. In Proceedings of the 2014 Conference on Interactive Entertainment, Proceedings of the 2014 Conference on Interactive Entertainment (IE2014), Newcastle, New South Wales, Australia, 2014; Association for Computing Machinery (ACM): New York, New York, United States, 2014; 1–8.
36. Agić, A.; Murseli, E.; Mandić, L.; Skorin–Kapov, L. The impact of different navigation speeds on cybersickness and stress level in VR. *Journal of Graphic Engineering and Design* 2020, *11*(1), 5–11.
37. Ronchi, E.; Kuligowski, E.; Nilsson, D.; Peacock, R.; Reneke, P. Assessing the Verification and Validation of Building Fire Evacuation Models. *Fire Technology* 2014, *52*(1), 197–219.
38. Lord, J.; Meacham, B.; Moore, A.; Fahy, R.; Proulx, G. *Guide for evaluating the predictive capabilities of computer egress models NIST GCR 06-886*. National Institute of Standards and Technology: Gaithersburg, Maryland, United States, 2005.
39. Galea, E. R. *Validation of evacuation models*. CMS Press: London, United Kingdom, 1997.
40. Gwynne, S.; Kuligowski, E.; Nilsson, D. Representing evacuation behavior in engineering terms. *Journal Of Fire Protection Engineering* 2012, *22*(2), 133–150.
41. Lovreglio, R.; Kuligowski, E.; Gwynne, S.; Boyce, K. Corrigendum to "A pre-evacuation database for use in egress simulations" [Fire Safety J. 105, 2019, 107-128]. *Fire Safety Journal* 2019, *108*, 102829.
42. Thompson, P.; Nilsson, D.; Boyce, K.E.; McGrath, D. Evacuation models are running out of time. *Fire Safety Journal* 2015, *78*, 251–261.
43. Kubíček, P., Stachoň, Z., Apeltauer, T., Apeltauer, J., Šašinka, Č., Snopková, D., et al. (2020). Testing the behavior of people in virtual and real environments - evaluation study [in Czech]. Brno.
44. Stachoň, Z., Snopková, D., Juřík, V., Ugwitz, P., Jochecová, K., Švedová, H., Kvarda, O., Šašinková, A., Kubíček, P., Apeltauer, T., Ježek, S., Šašinka, Č. (Manuscript). The Opportunities and Limits of Using Virtual Environments in Research on Wayfinding.
45. Lovreglio, R., Ronchi, E. & Kinsey, M.J. An Online Survey of Pedestrian Evacuation Model Usage and Users. *Fire Technol* 2020, **56,** 1133–1153. https://doi.org/10.1007/s10694-019-00923-8
46. Thunderhead Engineering: Pathfinder - User Manual. [online], [cit. 2021-08-31]. Retrieved from: https://support.thunderheadeng.com/docs/pathfinder/2021-2/user-manual/?_ga=2.170250851.213835569.1629969371-428854837.1627796180&_gac=1.159608271.1629969371.CjwKCAjw95yJBhAgEiwAmRrut-GwxR5c6dF2hAvQ9vJnXaNUhp01IzkFnG6WObXHwaXzEFKBcqD-MdRoCg38QAvD_BwE
47. Hart, P. Nilsson, N., Raphael, B. A Formal Basis for the Heuristic Determination of Minimum Cost Paths. IEEE Transactions Systems Science and Cybernetics 1968, 4, 100–107.
48. Thunderhead Engineering: Pathfinder - Technical Reference Manual. [online], [cit. 2021-08-31]. Retrieved from: https://support.thunderheadeng.com/docs/pathfinder/2021-2/technical-reference-manual/?_ga=2.183466597.213835569.1629969371-428854837.1627796180&_gac=1.158927304.1629969371.CjwKCAjw95yJBhAgEiwAmRrut-GwxR5c6dF2hAvQ9vJnXaNUhp01IzkFnG6WObXHwaXzEFKBcqD-MdRoCg38QAvD_BwE
49. Mizuchi, Y.; Inamura, T. Evaluation of human behavior difference with restricted field of view in real and VR environments. In *2018 27th IEEE International Symposium on Robot and Human Interactive*

Communication (RO-MAN), Proceedings of the 27th IEEE International Symposium on Robot and Human Interactive Communication, Nanjing, China, 201; 196–201.

50. Shi, Y.; Du, J.; Ahn, C.R.; Ragan, E. Impact assessment of reinforced learning methods on construction workers' fall risk behavior using virtual reality. *Automation in Construction* 2019, *104*, 197–214.
51. van der Ham, I.; Faber, A.; Venselaar, M.; van Kreveld, M.; Lãffler, M. Ecological validity of virtual environments to assess human navigation ability. *Frontiers In Psychology* 2015, *6*.
52. Lessels, S.; Ruddle, R. Three Levels of Metric for Evaluating Wayfinding. *Presence: Teleoperators And Virtual Environments* 2006, *15*(6), 637–654.
53. Marín-Morales, J.; Higuera-Trujillo, J.; De-Juan-Ripoll, C.; Llinares, C.; Guixeres, J.; Iñarra, S.; Alcañiz, M. Navigation Comparison between a Real and a Virtual Museum: Time-dependent Differences using a Head Mounted Display. *Interacting With Computers* 2019, *31*(2), 208–220.
54. Higuera-Trujillo, J.L.; López-Tarruella Maldonado, J.; Llinares Millán, C. Psychological and physiological human responses to simulated and real environments: A comparison between Photographs, 360° Panoramas, and Virtual Reality. *Applied Ergonomics* 2017, *65*, 398–409.
55. Uhlík, O.; Apeltauer, T. Analysis of reaction time in the protection of soft targets in the conditions of the Czech Republic [in Czech]. *Silnice a železnice* 2019, *5*, 122–129.
56. Naili, M.; Naili, M.; Bourahla, M. Stability-based model for evacuation system using agent-based social simulation and Monte Carlo method. *International Journal Of Simulation And Process Modelling* 2019, *14*(1), 1.
57. The R Project for Statistical Computing. Available online: https://www.R-project.org/ (accessed on 31. 8. 2021)
58. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag: New York, New York, 2016.

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